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Cassava Leaf Disease Prediction Using Efficientnet-B0 Model

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Abstract

The FAO estimates that 60 percent of the world's population makes their living from agriculture. The rapid increase in the global populations demand for food is also quite fast. In this case, plant diseases pose a substantial threat to the agricultural industry. Therefore, deep learning algorithms are applied to spot them at an early stage as a move towards protecting farmers against such losses while increasing crop yield. We applied CNNs in developing a technique for identifying different diseases of cassava leaf which lead to low yields. We created a cost-effective model that will help farmers to save costs and special- ize in farming operations. Early diagnosis of these diseases is proposed by EfficientNet-B0, which may serve well since they provide a remedy for minor cases of cassava leaf illnesses. This may lead to better cassava crop health, and therefore more food security especially in some particularly vulnerable places.

1. Introduction

The world's most extensively grown crop, cassava, grows best in tropical lowland regions; including South America, Eastern and Southeast Asia, East, West, and Central Africa, and South America. The primary problems of cassava producers concern fighting ill diseases while maximizing harvest results from both quality and quantity aspects. These diseases are generally identified visually by the farmers through their practical knowledge or experience. Thus, most of this approach is dependent upon individual skill and involves significant production losses due to wrong identification (Sambasivam and Opiyo).

The most common food crop that is consumed in Africa is cassava. It is the major source of energy for the people of Africa and can be eaten in various ways like raw, processed, etc. Cassava is also high in vitamins and proteins and most people consume regular vegetables. But the main problem with this plant is, it gets infected with various diseases and leads to loss of the crop. Cassava mosaic disease and cassava brown streak are the two diseases that are most frequently transmitted. Other diseases can affect this plant, but the most common ones are CMD and CBBD. Four different types of diseases are associated with cassava plants. The four different diseases have different symptoms and with the help of these symptoms, the model tries to extract the features and classify the image to the respective class (Rao) (Mathulaprangsan and Lanthong) (Ayu, Surtono, and Apriyanto).

The four different categories are:

1. Cassava green mite (CGM)
2. Cassava brown streak disease (CBSD)
3. Cassava mosaic disease (CMD)

4. Cassava bacterial blight disease (CBBD)

Each disease category has its symptoms like leaves are affected and roots affected the color of the leaves changes and the leaves shrink.

1. **Cassava green mite (CGM):** Although it is not considered a disease, infestations of Cassava Green Mite (CGM) can have effects, on cassava plants as they feed on the leaves and weaken them.
2. **Cassava Brown Streak Disease (CBSD):** It mainly affects the storage roots. It can also show symptoms on the leaves. It is caused by two virus species. This can result in root necrosis making the cas- sava roots unfit for consumption.
3. **Cassava Mosaic Disease (CMD):** This harmful ailment results in a pattern on the leaves. Certain kinds of begomoviruses cause it. poses a serious risk to cassava harvests.
4. **Cassava bacterial blight disease (CBBD):** The storage roots of cassava plants are the primary target of the pathogenic virus known as cassava brown streak disease (CBSD). The two viruses that cause it are the cassava brown streak virus (CBSV) and the Ugandan cassava brown streak virus (UCBSV). In regions where cassava is the principal crop, CBSD can result in root rot, make cassava roots inedible, and provide a major food danger.

In this work, we seek to present a summary of our methodology, covering the techniques we used, the data collection procedures, the CNN model's architecture, and the experimental results. Improving the identification of cassava diseases in global contexts is our main objective (Emuoyibofarhe et al. Ram- Charan Coulibaly et al.).

2. Literature Review

To obtain accurate results, different writers have used different models in this summary of studies on disease detection in leaves. CNNs, separable convolutions, VGGs, ResNet, DenseNet, MobileNetV2, Inception V3 transfer learning, fully connected neural networks, and customized 15-layer CNNs are some examples of these models. The accuracy percentages that have been attained vary from approximately 61.6% to 95%. Additionally, several writers have reduced log loss and greatly increased accuracy by using techniques for data rectification and augmentation. All things considered, these studies show a variety of methods and useful models used for the critical issue of plant disease identification.

Compared to the previously described algorithms, our EfficientNet-B0 model not only requires less processing time but also benefits from a larger collection of photos. Its outstanding success in plant disease identification can be attributed to its efficiency and large dataset (Abdullakasim et al.).

3. Proposed Methodology

3.1. Dataset

The data collection utilized to detect cassava leaf disease is obtained from Kaggle. The 21,397 photos with a resolution of 224x224x3 from the cassava leaves collection are used in this study.

We chose EfficientNet for transfer learning since it outperforms other benchmark models such as VGG, ResNet, DenseNet, etc., and may reduce the number of parameters required for training. To improve accuracy and efficiency, segmentation is also employed to eliminate leaves from the backdrop.

In the multi-label classification task, five output categories—four for illnesses and one for healthy leaves—were used. The following lists each cate- gory's label to illness mapping (Anitha and Saranya)

0: "Cassava Mosaic Disease (CMD)"
1: "Cassava Green Mottle (CGM)"
2: "Cassava Brown Streak Disease (CBSD)"
3: "Cassava Bacterial Blight (CBB)"
4: "Healthy"

Among the collections are 2,577 photographs for the healthy leaf class, 2,189 images for CBSD, 2,386 images for CGM, 13,158 images for CMD, and 1,087 images for CBB.

There are five distinct files containing the JPEG format photographs that were all taken. Each file consists of one type of disease, in this way, we can train the model more efficiently and the model can be trained accurately and can predict the disease accurately (Lee et al.).

3.2. Data Preprocessing

There are some challenges with our dataset. The first one was, that the size of the dataset was very small the second challenge was that the images didn't have clarity and the last challenge was the dataset was imbalanced, the CMD class has more images and CBB has less images (Anandkumar). The literature review is shown in Table (1).

The actions listed below were done to solve the mentioned problems: We attempted to use image augmentation to increase image contrast. You can use the image augmentation approach to make the dataset larger [17].

Table 1. Literature Review

Authors	Model Used	Results
G. Sambasivam et al., (Sambasivam and Opiyo)	CNN	Class-imbalanced rectification procedures improved accuracy by over 5% and decreased log loss to 0.06 percent from over 20% when enhanced data and big input image dimensions were used.
Patike Kiran Rao et al., (Rao)	Separable Convolutions UNet Fully Convolution Networks	83.9% and 61.6% accuracy rates, respectively
Seksan Mathulaprangsan et al., (Mathulaprangsan and Lanthong)	CNN VGGs ResNet DenseNet	DenseNet121 earned the maximum classification score of 80.52 percent. The accuracy of categorization has grown to 94.32 percent with the addition of brightness modification.
H. R. Ayu, & others (Ayu, Surtono, and Apriyanto)	The Graphical User Interface (GUI) of MobileNetV2	65.6% is the test data's total accuracy.
Ozichi Emuoyibofarhe and asso-cities, (Emuoyibofarhe et al.)	Support vector machine in cubic form (CSVM)	83.9 percent accurate and 61.6 percent accurate cubic support vector machine model
B. Ahmed, P. McCloskey, A. Ramcharan, and K. Bara-nowski (Ramcharan et al.)	Inception V3 transfer learning	Accuracy 93%
Coulibaly and others. (Coulibaly et al.)	CNN VGG16	95% accuracy
Abdullakim & associates. (Abdullakasim et al.)	Neural Network (NN) that is fully connected and has a single hidden layer	Accuracy: 89.92% of plants in good condition, 79.23% of leaves with sickness
Sangbamrung, Praneetpholkarang & Kanjanawat-tana (Anitha and Saranya)	Unique CNN with 15 Layers	0.96 is f-score

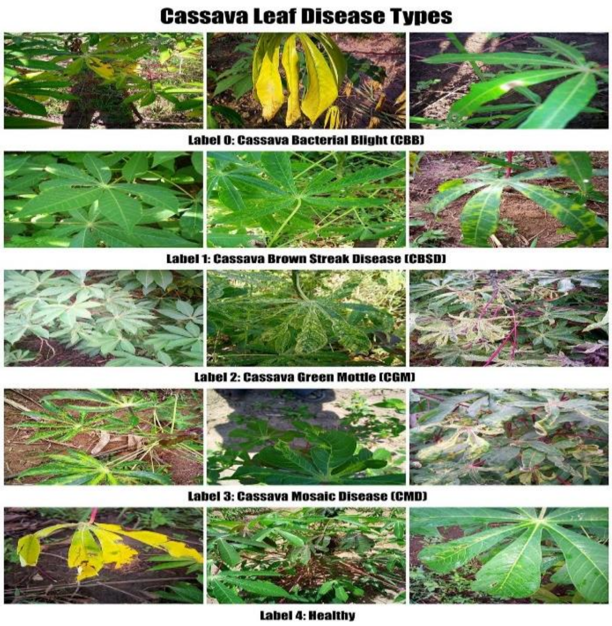

Figure 1. **Cassava Images**

Image augmentation is the process of creating new, slightly altered versions of images in a dataset by applying various modifications to those images. This technique is widely used in computer vision and machine learning to increase the diversity and size of training datasets, enhance model performance, and strengthen the robustness of machine learning models. We can perform new transformations on the images from the original data set that you give as input. During the model's training phase, real-time image augmentation can be carried out using Keras' Image Data Generator. This implies that every training image that is given into the model can have random changes done to it. This method not only improves the resilience of the model but also efficiently controls memory usage. Data augmentation broadens the training dataset, which improves Efficient-Net B0's performance. It is possible to employ methods such as rotation, flipping, cropping, resizing, brightness modifications, noise addition, and color changes. Data augmentation helps Efficient- Net B0, which is renowned for its efficiency, handle a wider range of picture data and generalize more successfully. The problem and particular dataset must be considered before selecting an augmentation strategy (Tan and Le Wang et al.). Cassava Images are shown in Figure 1.

• **Flips:** In image processing, a flip can be either a vertical or horizontal flip of an image. Whereas vertical flips switch an image's top and bottom, horizontal flips switch an image's left and right sides. To take into consideration the various orientations of the items in the dataset, they are employed.

Horizontal Flip: Flipping the image horizontally: **augmented image=**
flip horizontally (original image) ——(1)
Vertical Flip: Flipping the image vertically: augmented_image =flip_vertically (original image) ——(2)

• **Rotations:** A rotation is an angle at which an image's orientation is changed. This method is useful for achieving rotational invariance and aids models in learning to recognize things from different angles.

augmented_image = rotate (original image, angle=90) ——(3)

• **Shifts:** Typically, shifts in the context of image processing refer to spatial translations. These include shifting the whole image or a specific area of it in one or more directions (e.g., up, down, left, or right). To train a model to identify items in various locations inside an image (Wang et al.).

3.3. Proposed Model

It is a deep-learning model using CNN and based on EfficientNet B0. The neural network architectural family known as EfficientNet, which included EfficientNet B0, was initially introduced in Tan and Le's 2019 paper "EfficientNet: Re-thinking model scaling for convolutional neural networks.".Owing to the high efficacy and efficiency, these Efficient-

Net models have become popular in many computer vision applications [20].

The sequential model is mostly used if there is only one input layer and one output layer. It works efficiently for a single-layer architecture. Instead of creating the model from scratch, we used a pre-trained model called EfficientNet-b0. Along with improving the model's performance, this model can readily extract features from the provided photos (Rathore).

EfficientNet-b0 is a convolution neural network in which the model is trained with more than 10 lakh images using the ImageNet dataset. When it comes to recognizing and extracting features from input photos, our model excels. The maximum image size that it can handle is 224 x 224 pixels. Moreover, the model is pre-trained, indicating that it has previously acquired significant features from an extensive dataset, rendering it a beneficial foundation for constructing an optimal model for a range of computer vision applications.

We have employed the idea of pooling to further improve the model's performance. Pooling is a technique used to downscale the image by reducing the pixel density. There are different types of pooling techniques available and we used the max average pooling technique. This method uses a technique known as compound scaling.

Compound scaling is a technique used to simultaneously alter a deep learning model's depth (number of layers), breadth (number of channels), and resolution (size of the input image) to optimize performance while preserving computational economy. To obtain a desirable trade-off between model complexity and accuracy, this method is applied in models such as EfficientNet (Hillocks and Thresh).

The architecture of EfficientNet-B0 with MBConv as basic building blocks

A compound scaling approach is used to increase the size of the EfficientNet B0 architecture. By using a set of predefined scaling coefficients, this approach consistently scales the depth, width, and resolution of the network. This allows the network to be scaled up without sacrificing efficiency or accuracy. The EfficientNet B0 architecture has approximately 5.3 million parameters, which is significantly fewer than other state-of-the-art CNN architectures. EfficientNet-B0 Architecture is shown in Figure 2.

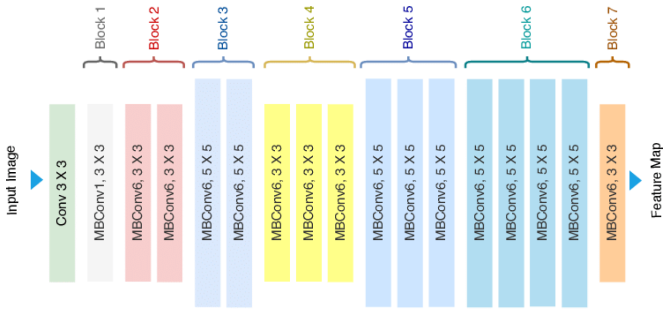

Figure 2. EfficientNet-B0 Architecture

This makes it a good choice for applications where computational resources are limited. It has been demonstrated that the EfficientNet B0 architecture can reach state-of-the-art accuracy on several picture classification tasks, including CIFAR-100, ImageNet, and Flowers. Additionally, it has demonstrated good transferability to other tasks including segmentation and object detection (Legg and Thresh).

3.4. Algorithm

3.4.1 Step 1 The input image is first resized to a resolution of 224x224 pixels.

Step 2 After that, the image is subjected to several convolutional layers to extract features.

Step 3 After that, the features are run through a sequence of inverted bottleneck residual blocks, which help to extract additional features and lower the representation's dimensionality. Step:4 After that, the features go through a sequence of squeeze-and-excitation blocks that enhance the network's functionality by suppressing less informative char-characteristics and highlighting valuable features.

Step 5 A global average pooling layer and one last convolutional layer are applied to the features.

Step 6 The ultimate output of the network is obtained by passing the global average pooling layer's output via a fully connected layer (Aristan and Kusuma).

3.5. Model Evaluation

Model evaluation is a crucial step in identifying and improving the model's performance. We used 16 and 20 epochs as our batch size. Another problem we identified is the overfitting of the model. We used the early stopping technique to resolve the problem. Throughout its 17 full training epochs, the model has improved in terms of both accuracy and loss.

We have also used the ReduceLROnPlateau approach to decrease the model's learning rate.

3.6. Analysis of the Overall Growth Trend

This section provides an overview of the primary findings from the bibliometric study, outlining the size of the collection in terms of the number of documents, authors, sources, keywords, timespan, references, and average number of citations (Abdullah, Alsalem, and Alqurashi). Moreover, numerous co-authorship indices are displayed. A summary of the main results of the bibliometric analysis is shown in Table 2.

Table 2. Summary of the main results of the bibliometric analysis

Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	1994:2023
Sources (Journals, Books, etc)	14
Documents	266
Annual Growth Rate %	5.71
Document Average Age	8.46
Average citations per doc	52.63
	13948
DOCUMENT CONTENTS	
	2080
Author's Keywords (DE)	637
AUTHORS	
Authors	1608
Authors of single-authored docs	2
AUTHORS COLLABORATION	
Single-authored docs	2
Co-Authors per Doc	7.36
International co-authorships %	54.51
DOCUMENT TYPES	
article	251
conference paper	4
review	11

3.7. *Performance Metrics*

In this work, the most popular criteria are utilized to evaluate the performance of the proposed model and the existing models for the classification of photos with cassava leaf disease.

Accuracy= (TP+TN) / (FP+FN+TP+TN) (4)

Precision= (TP) /(TP+FP) (5)

Recall = (TP)/(TP+FP) (6)

F1 score=2 * (Precision * Recall) / (Precision + Recall) (7)

- True Positives, or TPs, are instances where the model correctly predicts the positive class.
- The model produced False Positives (FPs) when it predicted the positive class incorrectly in certain instances.
- False Negatives (FN) resulted from the model's incorrect prediction of the negative class in these situations (Owolabi and Awoyemi).

3.8. Activation Function

The neural network model for our study made use of the "SoftMax" activation function. This particular activation function has been employed in the dense layer with five neurons. Because classification neural networks often use this design in their out-and-put layer, it is suitable for multi-class classification tasks. The "SoftMax" activation function is required to transform the layer's output into a probability distribution so that class probabilities for different categories can be determined. In our situation, the five neurons in this layer reflect the number of classes or categories in our classification task.

Thus, this configuration is a key part of our neural network model designed for tasks like photo classification or natural language processing, and it facilitates the prediction of class assignments for input data (Jha and Sharma).

4. Results

We plotted the model's accuracy and loss graphs using the Matplotlib tool, as shown in Figures 3 & 4.

By the testing process, we can observe that the accuracy is 90.85 %

As seen in Figures 3 and 4, the y- and x-axes represent the number of epochs, accuracy level, and loss level, respectively (Oluwatosin and Akanni).

Accuracy describes how accurately the model is predicting for each given input. As we can observe in the below graphs that in Fig 3, the training and validation accuracy is increasing for each epoch, and in Fig 4 we can observe, the training and validation loss is decreasing for each epoch (Effiong) (Opoku and Owusu).

5. Conclusion

To sum up, our study demonstrates how well the EfficientNet B0 architecture works in a CNN model

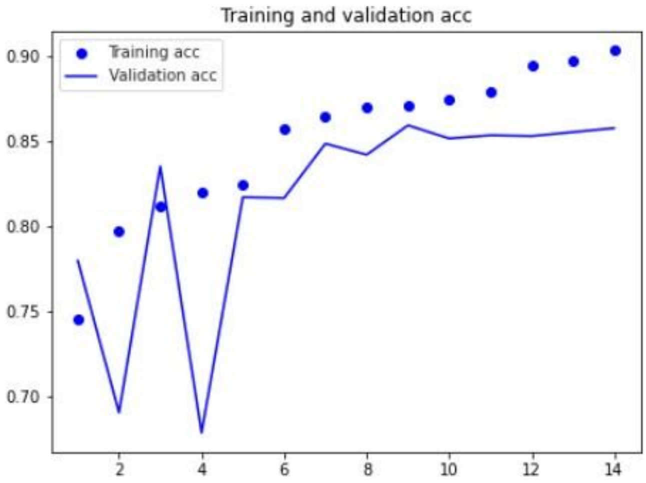

Figure 3. The above graph describes the accuracy of the model for the given training and testing (or) validation data.

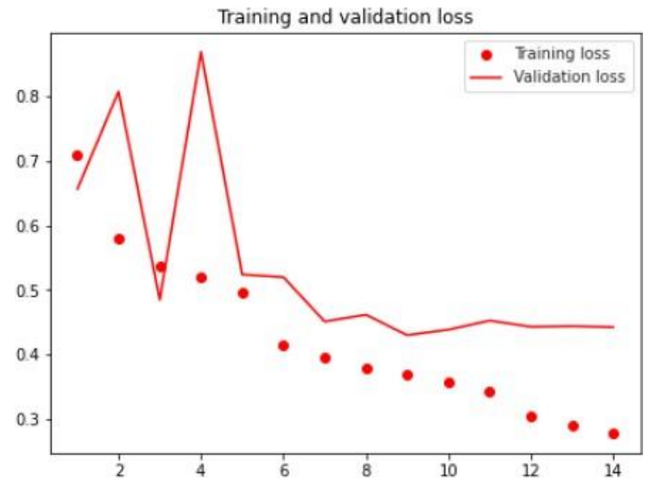

Figure 4. The above graph describes the loss of the model for the given training and testing (or) validation data.

to diagnose diseases of cassava leaves. The model has proven to be a reliable tool for the agricultural industry, especially for real-time applications, as seen by its strong performance in classifying healthy leaves and various illnesses. Our research highlights the potential benefits of combining AI with agriculture to improve crop health, production, and sustainability, as well as the adaptability of Efficient-Net B0 for computer vision applications. Subsequent investigations will build upon this framework by tackling supplementary ailments, augmenting the robustness of the model, and intensifying its applicability as a tool for agriculture, acknowledging the revolutionary possibilities of artificial intelligence in transforming farming methodologies and worldwide food security (Oladele and Oyekunle).

6. Future scope

Improved Accuracy: With advancements in deep learning and larger, more diverse datasets, we can expect even higher prediction accuracy. Edge Computing: As computational devices become more powerful, deploying CNN models on the edge (in field-deployed devices) will enable real-time, on-site disease diagnosis, making it accessible to remote agricultural regions. Mobile Applications: Integration of CNN-based cassava disease prediction into mobile apps will provide a user-friendly interface for farmers to take images of their cassava plants, receive instant disease assessments, and access resources for disease management.

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